10. Bright and wealthy: exploring assortative mating*

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10.1. INTRODUCTION

In his first work on marriage markets, Becker (1973) noted that sorting between traits of married couples is not a random phenomenon, since people prefer to match according to personal characteristics, like age, beauty, labour productivity and education. He coined the term assortative mating for the pattern of trait pairings between partners in a monogamous marriage market.

In a given marriage market, assortative mating can either be negative or positive. For example, assume that in a marriage market the only relevant trait in pairing is labour productivity: under positive assortative mating couples are formed by individuals endowed with similar levels of productivity, whereas under negative assortative mating they are formed by spouses whose productivity in labour activities tends to be different.1 If positive assortative mating prevails, the correlation between the spouses' productivity displays a positive sign and testifies to a tendency of likes to marry likes.

The issue of marital sorting is relevant to empirical research in economics since a high degree of assortative mating between partners in a given society reinforces income inequalities across families, impacts negatively on the returns of education, and on the probability of the children engaging in criminal activities (Ermisch et al., 2006; Fernández et. al., 2005; Ermisch and Francesconi, 2002; Fernández and Rogerson, 2001).

When it comes to matching on more than one variable – so-called *multidimensional sorting* – the interpretation of cross correlations becomes much more tricky. For example, a positive empirical relationship is usually observed between spousal education and one's earnings (Boulier and Rosenzweig, 1984; Benham, 1974) and identifying the exact nature of these cross effects can be highly problematic. On the one hand, game theorists (Roth and Sotomayor, 1990; Gale and Shapley, 1962) maintain that the outcome of the marriage market competition is such that the more educated members of one sex tend to marry the more educated members of the other: the observed cross correlations are simply a by-product of mating on education. On the other hand, spousal education may well help partners to accumulate human capital and increase earnings, since couples with high levels of education are more likely to share ideas, values and tastes within the family, and this homogeneity may impact positively also upon market productive traits (Huang et al., 2006). In a simple OLS regression context, the two models are observationally equivalent. The identification problems are similar to those found in the human capital literature with regard to alternative explanations for the positive correlation between schooling and earnings, i.e., a problem of mutual causation. Higher education could either signal high-skilled individuals, as in Spence (1973), or a deliberate attempt to increase the level of human capital, as in Becker (1964): when multiple causality exists, devising a test to disentangle the relative importance of selectivity from that of cross-productivity is an open issue, since finding genuinely exogenous instrumental variables is far from simple.

This chapter is an empirical study of multidimensional mating in the marriage market and its contribution is twofold. First, we point out that the marriage market jointly determines assortative mating on schooling *and* on wages, i.e., market and household productivity, because schooling and wages are only partly substitutable in the marriage market, as emphasized by the theory of compensating differentials (Grossbard-Shechtman and Neuman, 1988).

Secondly, we estimate a simultaneous equations model for the Italian marriage market in which schooling and market productivity are the main traits which jointly determine the pattern of marital sorting, along with a Mincer-like wage equation. To our knowledge, this estimation has not been attempted elsewhere. Assuming that prospective partners have rational expectations and private information on each other's traits that are revealed only gradually across time, we estimate a structural equation system which shows how marriage and labour markets interact. The data are extracted from the Bank of Italy's Survey on Household Income and Wealth (SHIW), with families tracked longitudinally from 1989 to 2006. The temporal structure of the dataset allows for an estimation of long-run performance in the job market and in the educational system which cannot be fully disclosed at the beginning of marriage, but whose expected value is relevant to spouse selection. Unfortunately, the SHIW dataset does not include information on family background and age at marriage: this precludes the possibility of systematically disentangling the effect of marital sorting at the time of marriage and intervening change along the life-cycle. To mitigate this identification problem, we compare a subsample of young couples to the whole sample: interestingly, we find that marital life does not radically change the pattern of mating as observed in the first years of marriage. This corroborates our initial hypothesis that the marriage market plays a significant role in determining social stratification.

Our key finding indicates that wage has predictive power in forecasting educational mating and that education also helps predict wage sorting. The inclusion of these cross variables significantly decreases the level of the observed univariate correlations in the data. Furthermore, we also investigate the issue of substitutability in depth using a non-linear model: we find that wage and schooling are substitutable inputs in men's search process, whereas the same inputs are complementary in women's search.

The chapter is organized as follows. The next section surveys the current literature on cross effects of wage and schooling between partners. Then we introduce a stylized model of the marriage market which can account for multidimensional sorting. Various estimates for the model are provided and the resulting evidence is discussed, along with possible directions for further research.

10.2. BACKGROUND LITERATURE

The study of spousal matching over personal traits has long been a topic of research in the fields of biology, economics and sociology. Epstein and Guttman (1984), in one of the most extensive studies to date on unidimensional sorting, observe positive assortative mating for ages, wages, education, religion, heights, IQ scores and ethnicity measured by robust statistical association. The applied economic literature on multidimensional sorting dates back to the work of Benham (1974) on the cross effects of education: he finds that wife's education increases husband's wage by 3 per cent in the US. According to Tiefenthaler (1997), wife's education increases husband's wage by 5–7 per cent in Brazil, while husband's education increases wife's wage by roughly 5 per cent, though his estimation does not explicitly control for sample selection due to assortative mating. Also, significant benefits are found to arise from role specialization in the family and job association, i.e., working in the same market sector. In their study on Chinese twins, controlling for selectivity in the marriage market and for family background, Huang et al. (2006) find that husband's education boosts wife's earnings by 3.5 per cent, but cannot find any effect running in the opposite direction. They provide evidence that the increase in wife's earnings is explained by a positive effect on hourly wages.

Empirical results invariably show a positive sign for the crude correlation between spouses' wages. In their study of assortative mating, Zhang and Liu (2003), correcting for sample selection and cross-productivity effects, find that the correlation between spouses' potential wages is not statistically significant, such that the main gains from marriage seem to derive from role specialization, as in Becker (1991[1981]). This evidence is partly consistent with the work of Smith (1979) who comes across low correlations between wage residuals once the estimation procedure takes into account sample selection. To date, the only result of negative assortative mating on wages has been obtained by Zimmer (1996) with a negative coefficient for North-American whites and a positive coefficient for blacks, even though Becker (1991[1981], pp. 118–9) cites unpublished negative coefficients obtained by Gregg Lewis. Grossbard-Shechtman and Neuman (1991), using the 20 per cent sample from the 1983 census of Israel, find evidence of reciprocal influence of spouses' levels of schooling and significant complementarities in earnings-related measures. Hours of work have also received interest within this research field: Pencavel (1998) tests whether market work hours of husbands and wives are correlated with their spouses' schooling levels. Using the 1990 census for the US, he finds that husbands' labour supply is weakly influenced by their wives' schooling, while women married to a college-educated man work 4 per cent fewer market hours than women married to high-school dropouts, and the effect is almost doubled when the couple have children aged less than six years. This suggests that college-educated husbands substitute some of their own hours of work with their wives' hours in the market.

According to another stream of literature, the process of mating involves variables which the researcher can with difficulty fully control for. In this perspective, unobserved components of educational and income mating are employed to make inferences about the systematic patterns of marriage. Rupert and Cornwell (1997) find weak evidence of cross-productive effects in marriage: according to their estimation based on the National Longitudinal Survey of Young Men, the marriage premium – the observed positive difference in the wage level between married and unmarried men – is attributable to unobservable individual effects that are correlated with marital status and wages. Nakosteen and Zimmer (2001), using unobservable components of hourly wages observed immediately after marriage, find evidence of positive assortative mating on the basis of earnings for the subjects observed in the Panel Study of Income Dynamics (PSID). Mating equations are also employed to estimate components of the human capital which do not fall into the category of formal schooling. Behrman et al. (1995) use an educational mating equation to estimate unobservable skills which are found to impact significantly on the wage of Indian husbands. In their recent contribution, Brynin and Francesconi (2004) extended the same econometric methodology to wives and found several measures of market success associated with unobservable components of human capital.

When datasets contain observations on the same people before and after marriage, it is also possible to test selectivity against cross-productivity, especially with regard to wages: to date, the only study in this fashion has been that of Nakosteen et al. (2004) who take advantage of a one-of-a-kind Swedish archive recording data for the entire workforce. They find evidence of positive correlations between wages before marriage, a result supporting the presence of positive assortative mating net of any cross-productivity effects. The authors also find that the strength of the correlation declines after marriage, possibly due to diminished specialization within the family.

In contrast to previous literature, this article argues that marital sorting operates not only along the educational dimension but also on the income dimension. However, since education and labour income are not perfectly correlated, both correlations need to be taken into account when studying marital sorting. In this perspective, we contribute to clarify a missing link in the applied literature between the job market and the marriage market, a point which recently received attention in a theoretical contribution by Chiappori et al. (2006). Up to now, joint estimation of market productivity and educational sorting for married couples has not been attempted. It will be the theme of the next sections.

10.3. THE MARRIAGE MARKET

The model of the marriage market presented here is based on the assumption that schooling produces monetary effects because more educated people usually have better jobs, obtain higher salaries on the job market, and have greater chances of moving upward socially (Kalmijn, 1994). Non-monetary effects also follow from schooling, since education generally provides broader perspectives on world visions and relaxes strictness from inherited cultural values. Married individuals can gain from their spouses' higher level of education because of the monetary and non-monetary benefits from schooling: couples in which both spouses share the same background values enjoy higher utility streaming from the production of household public goods. In an ideal setting in which schooling and wages were perfectly correlated with no significant heterogeneity between people, the same pattern of marital sorting would prevail with regard to education and wages since the choice variable of matching would really make no difference.

In contrast, the real world is characterized by imperfect correlations between schooling and wages: this impacts the labour market as well as the marriage market. Explanations for the imperfect correlation in the labour market are not particularly relevant to our intent, since here we focus on what happens in the marriage market and on the heterogeneity observed inside and among couples, but it must be taken into account when estimating a model for the marriage market. This heterogeneity in sorting patterns is mainly due to: (1) different personal tastes toward the monetary and the non-monetary benefits flowing from education, and (2) unobservable individual factors which the social scientist can with difficulty control for.

Assuming that utility is transferable between partners, as in the classical Becker model, partners can make themselves attractive by compensating a low level of a personal trait with a high level of another valuable personal trait. After marriage, this compensation can take the form of monetary transfers, like in the model of Grossbard-Shechtman and Neuman (1988), but to a certain extent this compensation of traits can also take place in the marriage market: for example, a prospective husband endowed with low market productivity could make himself more attractive when endowed with relatively higher education. If this holds true, schooling and income are partly substitutable in women's eyes. As a result, marital sorting happens not only along the educational dimension, but partly also on the income dimension. Multidimensional matching – with regard to education and job prospects – and simultaneity are the cornerstones of the present model. We also assume that, when people meet in the marriage market, they tend to form rational expectations on each other's chances to obtain education and wage. Obviously, any family can benefit from high levels of wage and from high levels of education, but imperfect correlation and personal tastes introduce the possibility of substitution between the two inputs of household production.

Formally, actual household production for a generic family can be written as

$$F = F(\mathbf{v}) \tag{10.1}$$

where F is the total value of household-produced goods,

$$\mathbf{v} \equiv [e_w \quad e_h \quad s_w \quad s_h]' \tag{10.2}$$

is a vector containing the levels of education (e) and levels of wages (s) of the wife (w) and husband (h). F is assumed to be increasing in the level of each observable independent variable. Further, assuming competition among women and among men to marry the best partners, the marriage market mechanism maximizes the sum of the expected value of (10.1) across all possible matches (Becker, 1973, pp. 82–84).

Competition in the marriage market is based on the assumptions that matching is not completely random and that potential partners are at least partially substitutable. Thus the possibility of marrying a man of a given educational level depends, among other things, upon a person's educational and wage levels. This systematic relation between one's traits and his/her partner's is termed mating function (or mating equation) and has been introduced in the context of family economics by Boulier and Rosenzweig (1984): basically, it represents a reduced form equation summarizing the outcome of the marital search process as a function of the searcher's personal traits. While the current literature on human capital (Brynin and Francesconi, 2004; Behrman et al., 1995) estimates mating functions only with regard to schooling, we allow for simultaneous determination of educational and income sorting. With all the assumptions previously stated, equilibrium in the marriage market can be represented by the following system of mating equations:

$$\mathbf{Dv}+\mathbf{X}'\beta+\mathbf{\Omega}=\mathbf{0} \tag{10.3}$$

where

$$\mathbf{D}\equiv\begin{bmatrix} 1 & -d_1 & 0 & -d_2 \\ -d_3 & 1 & d_4 & 0 \\ 0 & -d_5 & 1 & -d_6 \\ -d_7 & 0 & -d_8 & 1 \end{bmatrix} \tag{10.4}$$

is the matrix of coefficients for the endogenous variables, $\mathbf{X}$ is a matrix of exogenous variables, $\boldsymbol{\beta}$ is a vector of estimated parameters for the exogenous variables, and

$$\mathbf{\Omega}\equiv\begin{bmatrix}\omega_w^e & \omega_h^e & \omega_w^s & \omega_h^s\end{bmatrix}' \tag{10.5}$$

is a vector of i.i.d. error terms.

To make things clearer, let us consider only the first two mating equations for wife's education and wage. These equations can be written as:

$$e_w = d_1 e_h + d_2 s_h + \mathbf{x}_h^e \beta_h^e + \omega_w^e \tag{10.6}$$

$$s_w = d_5 e_h + d_6 s_h + \mathbf{x}_h^s \beta_h^s + \omega_w^s \tag{10.7}$$

where the β coefficients for the exogenous characteristics $\mathbf{x}$ are allowed to vary across equations. As shown previously, the hypotheses that

$$d_1 > 0 \tag{10.8}$$

$$d_6 > 0 \tag{10.9}$$

have been tested in the literature under the implicit assumption that $d_2 = d_5 = 0$ and found true. Instead, we are interested in testing whether

$$d_1, d_2 > 0 \tag{10.10}$$

$$d_6, d_5 > 0 \tag{10.11}$$

i.e., if there is any possibility of trade between schooling and market productivity. To sum up, this structure for marital mating is based on four equations: two for schooling of husbands and wives and two more for wages of the same spouses. Each mating equation implies that a man's wage and schooling jointly determine the expected levels of schooling and wage of his prospective wife, and the same causal relation holds true also for women. This implies the possibility that education and wage can impact differently upon the prospective spouse's wage and schooling.

This linear marriage market is exactly identified, since it is made up of four variables and four equations. However, wages and schooling levels are linked not only through the marriage market, but also through the labour market, for higher education implies higher wages. This is a potential source of collinearity which must be taken into account, due to its economic and statistical relevance. Accordingly, for both partners $i \in \{h, w\}$ of the j-th couple we must add a wage equation of the type

$$s_{i,j} = r_i e_{i,j} + \mathbf{y}_{i,j} \beta_i + \theta_{i,j} \tag{10.12}$$

where r is the return from education, $\mathbf{y}$ is a vector of controls, θ is an i.i.d. error term, and j represents the j-th observation. This wage equation is estimated jointly with the mating equation for wage and the mating equation for education, separately for each gender: accordingly, the estimated effects of schooling and wages on marital sorting are net of direct labour market effects from schooling to wages. Estimation of this equation system will be the subject of the next section.

10.4. ESTIMATION AND DATA

10.4.1. The Dataset

The data used for estimation originate from the Bank of Italy's Survey on Household Income and Wealth (SHIW) sample, containing observations on families and individual components tracked longitudinally from 1989 to 2006. Though SHIW's data collection actually dates back to 1977, it is only since 1989 that data on education have also been collected for non-working individuals. Apart from observations from 1977 to 1987, other groups were dropped: (1) couples for which education is missing, (2) couples for which job status is missing, (3) couples in which one or both spouses are retired, (4) couples in which husbands are older than 65 and wives are older than 60. All income and wealth measures are adjusted to 2006-equivalent euros. Education and wages are in logarithms, with the censoring point for wage (originally set equal to zero) being shifted by one euro to obtain non-missing values for predicted wages also in the case of non-working individuals. In our sample, 47 per cent of wives work and receive a salary, and 95 per cent of husbands.

10.4.2. Estimation Procedure and Technique

The estimation procedure designed to test for cross effects of schooling and income is structured as follows:

1. The first problem to tackle when estimating the effects of sorting on observed labour behaviour is to obtain reasonable estimates of the expectations of e_i and s_i as they enter the evaluation that prospective partners make while dating. We assume that prospective partners have rational expectations on each other's achievements, both in the educational system and in the job market, i.e.,

$$E_{t-1}\left[e_{i,t} \mid I_{t-1}\right] = e_{i,t} \tag{10.13}$$

$$E_{t-1}\left[s_{i,t} \mid I_{t-1}\right] = s_{i,t} \tag{10.14}$$

   where E is the expectation operator and I is the set of relevant information. This implies that the observed values in the data for e_i and s_i can be used to recover their expected levels, provided that some sort of temporal smoothing is operated to obtain the expected values as computed before marriage. Since the data in SHIW have a panel structure, i.e., repeated observations across the years for the same couples, we can exploit this feature to obtain estimates of the variables relevant to the mating system. For computing expected education, we use the maximum level of schooling actually observed in the data. For computing expected salary, we use the median salary, given the notorious asymmetry of this variable.
2. Since salary is not observed for people permanently unemployed or outside the workforce and using only observations for working partners would introduce sample selection bias, we use Heckman's model (Heckman, 1979) to account for censoring and estimate the potential logarithm of wage for non-working wives and husbands. Accordingly,

we set up a selection probit equation, whose dependent variable is a dummy for participation in the labour market, along with a wage equation which includes the inverse Mills ratio derived from the selection equation. Both equations are jointly estimated using Full Maximum Likelihood. The selection equation for wives includes age, age squared, dummies for maximum schooling level achieved, number of children and husband's wage. The squared terms account for the non-linearities in wives' behaviour.2 The regressors for wives' wages include dummies for maximum schooling level achieved, expertise, expertise squared, dummies for main professional qualification, and dummies for the productive sector. The equations for husbands parallel those for wives, except for spouse's wage and main professional qualification which are not included in the selection equation.

3. Exploratory analysis of the variables and their interactions is performed using conventional parametric and non-parametric statistics.
4. Using predicted wages, we perform a three-stage least squares (3SLS) procedure for a system of three equations: one mating equation for schooling, another mating equation for schooling, and a Mincer-like wage equation. This procedure is run separately for wives and for husbands. The 3SLS estimator iterates over the estimated disturbance covariance matrix and parameter estimates until the parameter estimates converge. As a comparison, we also re-estimate the system using a seemingly unrelated regression (SUR) technique to check whether simultaneity is an issue. Along with direct and cross effects, mating equations contain controls for personal wealth (approximated by home ownership and income from capital), the inverse Mills ratio to account for censoring, and job qualification.
5. Finally, we check the relationship in the educational mating equations between schooling and salary using a flexible functional form. This allows us to distinguish between complementarity and substitutability between the inputs used in the process of marital sorting.

10.5. RESULTS

10.5.1. Selection Model

The pattern of labour participation of wives is displayed in Table 10A.1. Participation in the labour market rises monotonically with schooling. Using the *no schooling* modality as the baseline, we find that obtaining a bachelor's degree increases the probability of participation by 16.8–0.6 = 16.2 per cent, while wives who finished high school register an increase of 46.8–0.6 = 46.2 per cent in the probability of participation compared to wives with no education at all. This information may help explain the pattern of participation of wives in the labour market when used jointly with data about wages.

The results from the Heckman model for sample selection, obtained by Maximum Likelihood Estimation and displayed in Table 10A.7, highlight the concave effect of age on the probability of entering the job market.3 While the model estimated for men is not particularly interesting given the small fraction of men outside the workforce, some insights can be derived from the model estimated for wives. For this sample we find a significantly negative impact of children on labour market participation. Interestingly, higher husband's wages tend to favour the wife's entry on the job market. While Becker (1991[1981]) argues that the higher the husband's wage, the lower must be wives' hazard in participation, Lam (1988) has proved that this only holds when household production does not include public goods. The positive estimated coefficient in the present model supports the hypothesis that labour participation decisions of Italian wives are mainly driven by public goods considerations. Education also has explanatory power in the participation equation. Compared to the omitted modality (no schooling at all), earning a BA increases the likelihood of participation by a factor of 1.7. By contrast, women endowed with low levels of schooling tend not to work outside the house: in any case, however, more education tends to increase participation in the labour market. Two factors can be used to explain this tendency: first, at low levels of schooling, women find it more profitable to specialize in household production; secondly, women with higher education may have a stronger preference toward working outside the home, since they may attach value to working *per se*.

Compared to husbands, the wives' wage equation shows that expertise exerts a somewhat weaker influence: this is testified by smaller linear and quadratic coefficients; both husbands and wives show the usual U-reversed pattern. This evidence is consistent with two main explanations: (1) women tend to retire earlier than men, thus leaving their jobs when their human capital is still relatively productive; (2) women's human capital depreciates at a slower pace than men's. If proved robust by more detailed analysis, not to be conducted here for reasons of overall consistency, this last insight may help redesign the current laws about mandatory retirement. Moreover, job qualification is also important for explaining wages. Here the omitted modality is worker. Compared to this baseline, wives gain 38.9 per cent more by becoming free-lancers, 81.2 per cent more by becoming entrepreneurs, and 29 per cent more by becoming executives. Using the same omitted variable for husbands, husbands gain the same as women by becoming executives, while the payoff from entrepreneurial and freelance activities is higher.

10.5.2. Exploratory Analysis

To check the basic relations between wages and schooling, pairwise unconditional correlations on the censored sample are listed in Table 10A.5 and contrasted with the coefficients calculated over the uncensored sample, reported in Table 10A.6. In the uncensored sample, the notional wages for women and men permanently out of work are estimated using Heckman's selection model.

In the censored sample, the correlation between spouses' schooling is around 63 per cent, a value somewhat higher than the average 50 per cent reported by Lam (1988) for the US, while the correlation between wages is 41 per cent. Correlations between education and wages are both remarkably similar across gender, amounting to 38 per cent. Inspecting correlations for the uncensored sample reveals some interesting facts. As expected, the linear relation between schooling levels remains constant, since the small discrepancy is due to missing data excluded from calculations. The returns from education for wives drop by 15.7 per cent, while husbands lose 3.6 per cent. The main result here is that wage correlation between spouses drops by 12.8 per cent.4 This suggests that the very choice of wives to enter the job market is highly dependent upon agreements made in the family and upon potential returns from schooling, which seem markedly low for non-working wives.

From inspection of mating patterns a question about causality naturally arises: to what extent is educational sorting determined by the marriage market or by cross-productive effects? To investigate the issue, Table 10A.4 collects figures for those who experienced a transition toward a higher level of schooling in the years under study. The tabulations reveal that educational levels remain almost completely stable for married people, with less than 1 per cent of the sample achieving higher education while married. In other words, couples tend to form only after the educational path ends. Obviously, the estimates do not account for censoring, since young couples face a positive probability of increasing education during their lifetime; however, the small numbers of transitions observed suggest that assortative mating is mainly determined in the marriage market and subsequent adjustments play a negligible role. A natural implication is that changes in the level of assortative mating observed during the life cycle are almost exclusively attributable to variations in wages and in returns from schooling.

Since we are interested not only in the strength of the linear relation between the variables, but also in whether and how this relation changes as we move toward the tails of the distributions, we employ the method of quantile regressions, as described in Koenker (2005). Figure 10.1 displays the relation between the logs of husband's wage and wife's wage, provided that both work in the marketplace, according to the relation

$$s_{w,i} = g\left(s_{h,i}\right) + \delta_i. \tag{10.15}$$

On the x-axis we have the quantiles of the dependent variable and on the y-axis the values of the corresponding estimated coefficient. The straight line is the value of the OLS estimator, being used as a benchmark, surrounded by confidence bands at 90 per cent. The kinked line, surrounded by grey-shaded confidence bands, shows the values of quantile regression coefficients obtained at different points of the distribution of the dependent variable.

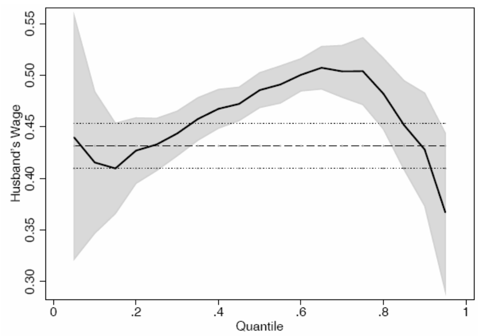

Figure 10.1: Correlation between spouses' wages (Censored sample)

Conditioning on wives' wage quantiles, the strength of the relation between the two variables displays a non-linear trend across the distribution, with steadily decreasing values until the last quantiles, where the relation jumps back to the same values observed for the low-wage wives. Point estimates of elasticities are always significantly greater than zero and range from 51 per cent at the third quartile to 37 per cent at the top quantiles and to 41 per cent at the lowest quantiles. The couples in which both partners work find that significant gains can be found in the central section of the distribution, even though the data do not allow the cross-productivity effects from assortative mating to be disentangled. However, the fact that the relation becomes weaker at higher quantiles suggests that both motivations become less important as wages go up. Most probably, when husband's wage goes up, the income effect induces substitution between partners' work efforts, resulting in higher levels of leisure enjoyed by women and decreased participation in the labour market.

Correcting for selectivity displays a relation between spouses' wages of increasing strength as we move upward to the distribution of the wife's wage, as is evident from Figure 10.2. The strength of this link becomes markedly lower at the first quantiles, dropping to 5 per cent. This is an interesting insight into the nature of matching, since it provides a new perspective on the age-old discussion of sorting between wages which cannot be obtained through OLS. Using a simple OLS estimator we would have incorrectly concluded that the coefficient is around 20 per cent, while this relation grows monotonically from 5 per cent at the lowest quantiles to 50 per cent at the top quantiles.

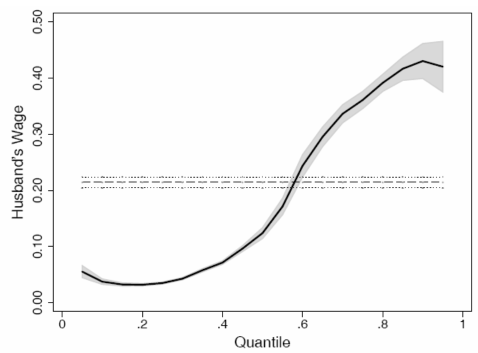

Figure10.2. Correlation between spouses' wages (Uncensored sample)

Finding 1 (Wage Sorting). *Focusing on the whole distribution of wages, Becker's conjecture that negative assortative mating is optimal looks partly confirmed.*

At low levels of wages Figure 10.2 shows that people tend to match according to the traditional model of labour division, such that the resulting sorting is very weak. Within these families, most of the gains from marriage derive from labour allocation between market and household production. By contrast, shifting to higher wages increases the possibility of enjoying higher levels of public goods, like child quality and leisure: accordingly, the level of positive assortative mating tends to increase. Comparison between Figures 10.1 and 10.2 reveals major differences due to the behaviour of non-working wives. Most likely, women tend not to work both when their husband's wage is very low and when it is very high: at very low wage levels, traditional roles may prevail, while at high wage levels women enjoy more leisure since they receive high monetary transfers from their husbands. At both tails of the distribution the same labour participation pattern of wives prevails, but for very different reasons.

10.5.3. Mating Equations

To develop some intuition about the interaction between schooling and wages, we start regressing the years of schooling of a partner i on the years of schooling of his/her partner j. Also, the same level of schooling is interacted with the quartiles of income of the j partner, according to the following equation

$$e_i = \sigma e_j + \sum_{q \in Q} \psi_{q,j} e_j s_{q,j} + \varepsilon_i. \tag{10.16}$$

If no interaction between wage and education is present, then we should find that $E[\psi_{q,j}] = 0$ for any $q \in Q$, where q are dummy variables for the q-th quartile of income. We estimate the equation for wives and husbands, using the full and the censored sample alternately. The results are reported in Tables 10A.8 and 10A.9, with the omitted variable being the first quartile of income from wage. Results show that $E[\psi_{q,j}] > 0$ in most of the estimates.5 In particular, husband's schooling interacts systematically with income in determining wife's schooling: compared to husbands in the first quartile, husbands in the fourth quartile register a 3 per cent increase in the elasticity of educational mating, both in the censored as well as in the full sample. Wives also follow a similar pattern, although at lower quartiles the estimated parameters of interaction are noisy, probably due to a higher proportion of notional wages. Our results suggest that educational mating interacts systematically with income and that people in the upper wage quartiles tend to display higher levels of educational homogamy.

Tables 10A.10, 10A.12, and 10A.14 show the results for the estimation of the complete structural model, both for husbands and wives of all ages, while Tables 10A.11, 10A.13, and 10A.15 contain estimation results for the subsample of husbands aged 16–35 and wives aged 16–33. The observations for non-working husbands were omitted from this estimation because of the very small fraction of men permanently out of work. Given the possible non-linearities between levels of education, we also estimated an alternative specification with quadratic terms for the years of schooling. Moreover, both these specifications – the linear and the quadratic – are carried out over the censored sample and over the uncensored sample. This was done since non-participation in the labour market is pervasive for wives and a significant fraction of their wages is notional. Consequently, estimates for wives should be considered with care and our comments will mainly focus on the estimates for husbands.

Finding 2 (Overall Fitting). *Estimation results of the full structural model show that the relation between spousal wages is modest, while the relation between spousal schooling levels is strong. This evidence weakly supports* *the Beckerian analysis which implies a low level of predictive power of wages for matching.*

The results show overall significance for both structural models. The R^2s statistics display acceptable values for the fitting of the educational mating equations (around 40 per cent) and low values for the wage equation.

Finding 3 (Returns to Schooling). *Own schooling impacts husbands' wages, while wives' schooling has a much noisier effect on their own wages.*

Most probably, women's choice of participation in the job market and carrier choice do not closely follow the educational background and are much more family-dependent, when compared to men's choices.

Finding 4 (Direct Effects). *The strongest effects of years of schooling and wage are direct ones: schooling of one partner helps predict the schooling of the other partner and wage of one partner helps predict the wage of the other.*

According to the schooling mating equation displayed in Table 10A.10, considered in its linear specification, the elasticity of an additional year of schooling, calculated around the mean, increases the prospective partner's schooling by 0.56–0.63. In the quadratic specification, the quadratic term and the linear term for schooling are found positive, such that we can conclude that the strength of educational sorting increases with the level of own schooling. According to the wage mating equation, the elasticity of an additional euro of own wage increases the prospective partner's wage by 0.52–0.63 in the uncensored sample and by 1.1 in the censored sample. This difference can be rationalized as follows: since the uncensored sample contains a large fraction of wives who choose not to work because of their low reservation wage and then prefer specialization in household production while their husbands do not, the impact of labour market productivity, approximated by the wage, is lower for the whole sample.

Finding 5 (Cross-Effect of Wage). *In the mating equation for wife's schooling, the elasticity of the impact of husband's wage is positive, ranging from 0.06 to 0.13. This is evidence that prospective husbands can partially compensate low schooling with high wages.*

The value of cross-elasticity signals that wage and schooling are at least partially substitutable in determining the prospective partner's education: this validates our initial intuition about the functioning of the marriage market. Interestingly, the effect of wife's wage on husband's schooling is stronger, as is evident from Table 10A.12 which shows that women with high wages tend to marry highly educated men. In a sense, with marriage, women's wage buys more education than men's. Compared to men, women are likely to be more interested in sharing values, tastes, and intellectual background because they attach less weight to traditional divisions of labour inside the household and more weight to the production of household public goods, like children's education; moreover, the strength of this effect grows stronger as the wife's wage goes up.

Finding 6 (Cross-Effect of Schooling). *While the effect of husband's schooling on his prospective bride's wage is noisy in the linear specification, in the quadratic specification, the quadratic term is positive while the linear term is negative. In contrast, wife's schooling shows an elasticity of 0.103–0.362 in predicting husband's wage* (see Table 10A.17).

This means that the effect of schooling is positive only after a given threshold which is equal to $e^{0.431/2\times 0.107} \approx 7.5$ years of schooling for the censored sample and to $e^{0.378/2\times 0.092} \approx 7.8$ years of schooling for the uncensored sample. These figures suggest that, apart from people who did not finish secondary school, a higher level of completed education is able to buy partners with a higher level of wage.

The issue of simultaneity is also relevant to our results: using as a benchmark a companion model of the same three equations obtained through the seemingly unrelated regression (SUR) technique reported in Table 10A.14, assuming only links between error terms and not between variables, the 3SLS-estimated equations display non-trivial differences between estimated coefficients, especially with regard to cross effects. This also supports our initial conjecture that wages and education jointly impact the sorting between spouses and that simultaneity does matter because (1) the marriage market has margins for substitution between wage and schooling, and (2) the marriage market and the labour market are closely linked.

Tables 10A.16 and 10A.17 compare several estimates over the whole sample to the same estimates over the sample of young couples: the exercise is interesting since young couples' traits in terms of schooling and wage are closer to the original traits found in the marriage market. Some interesting patterns emerge. Since all the variability in assortative mating during life is due to changing job conditions and not to changes in schooling and men experience more variability than women, the effect of wife's schooling on husband's schooling is stable around 0.550–0.609, while the husband's estimated effect lies between 0.484 and 0.653.

Finding 7 (Matching on Wages Across Lifetimes). *The degree of assortative mating on wages varies across lifetimes. The difference between the whole sample and the young sample degree of assortative mating on wage is around +0.268. For husbands, the change is around +0.131.*

10.5.4. More on Substitutability

Linear specification of the model, while permitting an appreciation of the process of marital sorting, cannot be used to investigate the issue of substitutability in depth. In the linear model, as the cross derivatives of the mating function with regard to the partner's education or wage are always zero, it is impossible to test whether schooling and wage are substitutable or complementary inputs in the matching process.

To deal with this issue, non-linear specification is needed to allow for more flexible determination of cross derivatives. With this intent, we picked the constant elasticity of substitution (CES) function. Within this scheme, the mating equation can be written as:

$$e_j = \lambda\left[\theta e_i^{\eta} + (1-\theta)s_i^{\eta}\right]^{1/\eta} \tag{10.17}$$

with $i,j \in \{h,w\}$ and $i \neq j$. Parameter θ is a distribution factor, while the elasticity of substitution σ between e_j and s_j can be derived according to the formula $\sigma = 1/(1-\eta)$. When $\sigma = 0$, that is $\eta \to -\infty$, the factors are perfect complements, while when $\sigma \to \infty$, which corresponds to $\eta = 1$, the factors are perfect substitutes. The case $\sigma = 1$ corresponds to the Cobb–Douglas function.

We estimate the schooling mating equation for husbands and wives in two different specifications. In the first, we estimate only the CES function through the non-linear least squares (NLS); in the second, we add a linear equation explaining wages with the level of schooling and estimate the system of equations using the non-linear seemingly unrelated method (NLSUR). The results are displayed in Tables 10A.18–10A.21. The first two columns contain the estimates for wives' schooling, the second two for husbands'. The first and third columns report the estimates for the NLS model, while the second and fourth do likewise for the NLSUR model. Estimation is performed both for schooling and wage mating.

Finding 8 (Complementarity and Substitutability). *Non-linear estimation shows that schooling and wage are substitutes for wives, while the same variables are (weak) complements for husbands.*

The search technology of husbands for their wives' schooling exhibits an elasticity of substitution of 0.62–0.76; similar figures are found for the wage mating equation. This can be taken as evidence of a tendency toward complementarity. The search technology of wives for their husbands' schooling lies between 1.36 and 3.33, while in the wage mating equation the elasticity varies between 1.53 and 5.25, which testifies a tendency toward substitutability. Most likely, family organization is important for matching and helps explain this asymmetric evidence. Women who do not participate in the job market are more interested in their husbands' wage than women working outside the household. Consequently, men who are interested in these women perceive that income from labour and schooling must complement each other to obtain a good match. By contrast, as women are not generally expected to be the main earner in the household, they can trade education and wage more easily. Quite interestingly, the NLSUR model provides higher values when compared to the NLS model.

10.6. FINAL REMARKS

In this chapter we tackled the role of education and wages in determining the level of assortative mating between partners. Since correlation between wages and education is far from perfect, we explicitly took both of them into account, along with the conventional wage equation commonly employed in the labour economics literature. Using data from Italian couples, we did find evidence that wages and education simultaneously determine how people match. We also found evidence of non-trivial differences in the mating behaviour between men and women.

It is also instructive to compare our results with those obtained by Behrman et al. (1995) and Brynin and Francesconi (2004), who apply the following mating equation:

$$e_w = d_1 e_h + \mathbf{x}_h^e \beta_h^e + \phi + \omega_w^e \tag{10.18}$$

where ϕ is an unobservable component of human capital to be estimated consistently from the post-regression residuals $\hat{e}_w - e_w$. They find that ϕ impacts positively on wages. Our results show that part of this unobservable variable depends upon wage, since marital sorting is multidimensional and education is not the only variable that prospective spouses may consider. If our interpretation holds true, then the expected return of unobservable human capital to wages should be lower than Behrman's estimates.

Lastly, an obvious way to enhance the present econometric exercise to take into account how mating coefficients change across the distribution of personal traits would be to employ a technique of simultaneous quantile regressions, as indicated by Chernozhukov and Hansen (2006) and Kim and Muller (2004): although still in its infancy, this approach looks extremely promising for modelling complex non-linear links like those observed in the marriage market.

10A. APPENDIX

10A.1. Statistical

10A.1.1. Descriptive statistics

Table 10A.1. Wife's education and job status

	Wife's working status					
	Working		Not working		Total	
Wife's education	Row %	Col %	Row %	Col %	Row %	Col %
No schooling	9.8	0.6	90.2	3.5	100.0	2.4
Elementary	17.3	9.9	82.7	30.2	100.0	22.3
Secondary	30.4	25.9	69.6	37.9	100.0	33.2
High school	54.8	46.8	45.2	24.7	100.0	33.3
BA/Postgrad.	74.0	16.8	26.0	3.8	100.0	8.9
Total	39.0	100.0	61.0	100.0	100.0	100.0

Table 10A.2. Husband's characteristics and wife's job status

	Wife's working status					
	Working		Not working		Total	
	Row %	Col %	Row %	Col %	Row %	Col %
Husband's education						
No schooling	15.6	0.7	84.4	2.4	100.0	1.7
Elementary	20.5	10.2	79.5	25.3	100.0	19.4
Secondary	35.0	31.6	65.0	37.4	100.0	35.2
High school	48.7	42.2	51.3	28.4	100.0	33.8
BA/Postgrad.	60.1	15.3	39.9	6.5	100.0	9.9
Total	39.0	100.0	61.0	100.0	100.0	100.0
Quartiles of husband's wage						
No schooling	36.2	23.2	63.8	26.1	100.0	25.0
Elementary	41.8	26.8	58.2	23.9	100.0	25.0
Secondary	34.6	22.3	65.4	26.9	100.0	25.1
High school	43.3	27.7	56.7	23.1	100.0	24.9
BA/Postgrad.	39.0	100.0	61.0	100.0	100.0	100.0
Total	39.0	100.0	61.0	100.0	100.0	100.0

Note: The table contains (1) percent distribution of job status of wives according to the level of completed education of their husband and (2) percent distribution of job status of wives according to the quantiles of their husband's income. All values are calculated over the working life cycle.

Table 10A.3. Husband's and wife's educational sorting

	Husband's education						
Wife's education	No Schooling	Elementary	Secondary	High school	BA/Post -grad.	Total	**N**
No schooling	32.3	48.5	16.0	3.0	0.2	100.0	468
Elementary	3.2	57.7	30.5	8.2	0.4	100.0	4,430
Secondary	0.7	12.9	56.4	28.2	1.9	100.0	6,602
High school	0.0	3.3	26.2	57.3	13.1	100.0	6,627
BA/Postgrad.	0.0	0.3	6.0	39.2	54.5	100.0	1,762
N	339	3,861	6,994	6,724	1,971	19,889	

Note: The cells of the table represent the fraction of the married couple sharing a given combination of schooling. Along the main diagonal is the percent of married couples sharing the same schooling level, i.e. those which are perfectly matched.

Table 10A.4. Schooling Transitions over the Lifetime

	Husbands			
Wives	None	One	Two	Total
None	97.66	0.95	0.00	98.61
One	0.87	0.49	0.01	1.37
Two	0.01	0.01	0.00	0.02
Total	98.54	1.45	0.01	100.00

Note: Every cell of the table contains the total percentage of lifetime transitions toward higher levels of schooling. The percentage of people who experienced schooling transition when married is extremely low.

10A.1.2. Correlations

Table 10A.5. Correlations – Censored Sample

Variables	Wife's schooling	Husband's schooling	Wife's wage	Husband's wage
Wife's schooling	1.000			
Husband's schooling	0.645	1.000		
Wife's wage	0.382	0.306	1.000	
Husband's wage	0.306	0.388	0.412	1.000

Table 10A.6. Correlations – Uncensored Sample

Variables	Wife's schooling	Husband's schooling	Wife's wage	Husband's wage
Wife's schooling	1.000			
Husband's schooling	0.630	1.000		
Wife's wage	0.225	0.178	1.000	
Husband's wage	0.270	0.361	0.281	1.000

10A.2. Estimation Results

10A.2.1. Heckman selection model

Table 10A.7. Wives

	Coefficients			Stats	
Variables	β	s.e.	Sig.	Mean	σ
Dependent variable: wife's wage					
Elementary	0.004	0.074		0.217	0.412
Secondary	0.004	0.075		0.332	0.471
High school	–0.060	0.078		0.338	0.473
Bachelor	0.109	0.080		0.089	0.284
Postgraduate	0.068	0.134		0.002	0.044
Expertise	0.017	0.003	***	24.392	10.825
Expertise (Square)/100	–0.014	0.005	**	7.121	5.629
White collar/Teacher	0.227	0.015	***	0.230	0.421
Executive	0.290	0.029	***	0.016	0.125
Freelancer	0.388	0.050	***	0.005	0.073
Entrepreneur	0.812	0.139	***	0.014	0.119
Self–employed	0.114	0.094		0.080	0.272
Manufacturing	0.519	0.029	***	0.099	0.298
Marketing/Catering	0.476	0.031	***	0.088	0.283
Transportation/Communications	0.542	0.047	***	0.008	0.088
Finance	0.652	0.039	***	0.016	0.125
Public administration/Service	0.580	0.029	***	0.243	0.429
Outside workforce	0.021	0.041		0.524	0.499
Constant	5.361	0.084	***		
Selection Equation					
Age	0.110	0.009	***	40.671	8.982
Age (Square) / 100	–0.135	0.011	***	17.348	7.341
Elementary	0.246	0.084	**	0.217	0.412
Secondary	0.598	0.083	***	0.332	0.471
High school	1.173	0.083	***	0.338	0.473
Bachelor	1.693	0.088	***	0.089	0.284
Postgraduate	1.576	0.224	***	0.002	0.044
Number of children	–0.116	0.009	***	1.679	1.079
Husband's wage	0.051	0.003	***	4.323	2.767
Constant	–3.274	0.188	***		
tanh(ρ) Constant	–1.184	0.035	***		
ln(σ) Constant	–0.520	0.014	***		
Statistics					
Subjects	19,888				

Notes:
p-value thresholds: * < 5%, ** < 1%, *** < 0.1%.
Omitted modality for education: no schooling.
Omitted modality for professional qualification: worker.
Omitted modality for sector: agriculture.

10A.2.2. Interaction wage–schooling

Table 10A.8. Husbands: interaction schooling–wage

	Coefficients			Stats		
Variables	β	s.e.	Sig.	β	s.e.	Sig.
Wife's schooling	0.560	0.011	***	0.613	0.021	***
Schooling * 2nd income quartile	0.002	0.003		–0.003	0.005	
Schooling * 3rd income quartile	–0.011	0.003	***	0.004	0.004	
Schooling * 4th income quartile	0.030	0.002	***	0.029	0.004	***
Constant	1.022	0.026	***	0.892	0.050	***
Statistics						
Subjects	19,888			7,754		
R^2	0.403			0.427		

Notes:
p-value thresholds: * < 5%, ** < 1%, *** < 0.1%.
Dependent variable: Husbands' years of completed schooling.
Years of schooling are in log units.

Table 10A.9. Wives: interaction schooling–wage

	Coefficients			Stats		
Variables	β	s.e.	Sig.	β	s.e.	Sig.
Husbands' schooling	0.636	0.013	***	0.589	0.021	***
Schooling * 2nd income quartile	0.023	0.004	***	0.016	0.004	***
Schooling * 3rd income quartile	0.034	0.003	***	0.029	0.004	***
Schooling * 4th income quartile	0.036	0.004	***	0.033	0.005	***
Constant	0.749	0.028	***	0.990	0.048	***
Statistics						
Subjects	19,888			7,754		
R^2	0.401			0.426		

Notes:
p-value thresholds: * < 5%, ** < 1%, *** < 0.1%.
Dependent variable: Wives' years of completed schooling.
Years of schooling are in log units.

Table 10A.10. Full structural estimation for husbands – 3SLS estimator

	Linear specification						Quadratic specification					
	Cens. sample			Uncens. sample			Cens. sample			Uncens. sample		
	β	s.e.	Sig.	β	s.e.	Sig.	β	s.e.	Sig.	β	s.e.	Sig.
Mating equation for schooling												
Dependent variable: wife's schooling												
Husband's schooling	0.556	0.014	***	0.633	0.010	***	0.408	0.042	***	0.371	0.026	***
Husband's wage	0.155	0.019	***	0.131	0.015	***	0.134	0.020	***	0.071	0.016	***
Husband's schooling (square)							0.037	0.010	***	0.075	0.007	***
Constant	0.172	0.095		0.024	0.076		0.430	0.122	***	0.572	0.093	***
Mating equation for wage												
Dependent variable: wife's wage												
Husband's wage	1.050	0.073	***	0.525	0.038	***	1.125	0.070	***	0.632	0.036	***
Husband's schooling	0.027	0.030		–0.028	0.012	*	–0.431	0.074	***	–0.378	0.027	***
Husband's schooling (square)							0.107	0.018	***	0.092	0.008	***
Constant	0.178	0.320		3.089	0.171	***	0.308	0.338		2.877	0.173	***
Wage equation												
Dependent variable: husband's wage												
Husband's schooling	0.313	0.017	***	0.246	0.010	***	0.318	0.017	***	0.262	0.010	***
Constant	4.588	0.053	***	4.777	0.033	***	4.568	0.053	***	4.734	0.033	***
Control for qualification	Yes			Yes			Yes			Yes		
Control for job sector	Yes			Yes			Yes			Yes		
Control for expertise	Yes			Yes			Yes			Yes		
Control for wealth	Yes			Yes			Yes			Yes		
Control for non-labour income	Yes			Yes			Yes			Yes		
Statistics												
Subjects	6,093			13,915			6,093			13,915		
R^2 1st equation	0.418			0.400			0.422			0.409		
R^2 2nd equation	0.064			–0.012			0.019			–0.092		
R^2 3rd equation	0.376			0.363			0.376			0.362		

Note: p-value thresholds: * <5%, ** < 1%, *** < 0.1%.

Table 10A.11. Full structural estimation for young husbands – 3SLS estimator

	Linear specification						Quadratic specification					
	Cens. sample			Uncens. sample			Cens. sample			Uncens. sample		
	β	s.e.	Sig.	β	s.e.	Sig.	β	s.e.	Sig.	β	s.e.	Sig.
Mating equation for schooling												
Dependent variable: wife's schooling												
Husband's schooling	0.521	0.028	***	0.472	0.019	***	1.165	0.167	***	0.261	0.051	***
Husband's wage	0.073	0.039		0.218	0.030	***	0.078	0.039	*	0.185	0.032	***
Husband's schooling (square)	–0.136	0.036	***	0.059	0.013	***						
Constant	0.786	0.196	***	–0.030	0.157		0.007	0.310		0.332	0.182	
Mating equation for wage												
Dependent variable: wife's wage												
Husband's wage	1.127	0.214	***	0.166	0.108		1.209	0.206	***	0.243	0.102	*
Husband's schooling	0.113	0.080		0.020	0.030		–0.935	0.394	*	–0.435	0.074	***
Husband's schooling (square)							0.221	0.086	**	0.123	0.020	***
Constant	–0.863	0.886		4.666	0.488	***	–0.000	1.095		4.660	0.481	***
Wage equation												
Dependent variable: husband's wage												
Husband's schooling	0.290	0.048	***	0.224	0.029	***	0.293	0.048	***	0.230	0.029	***
Constant	4.679	0.159	***	5.037	0.092	***	4.659	0.159	***	4.990	0.093	***
Control for qualification	Yes			Yes			Yes			Yes		
Control for job Sector	Yes			Yes			Yes			Yes		
Control for expertise	Yes			Yes			Yes			Yes		
Control for wealth	Yes			Yes			Yes			Yes		
Control for non-labour income	Yes			Yes			Yes			Yes		
Statistics												
Subjects	1,278			2,852			1,278			2,852		
R^2 1st equation	0.337			0.314			0.345			0.328		
R^2 2nd equation	–0.014			0.033			–0.058			0.031		
R^2 3rd equation	0.275			0.269			0.275			0.269		

Note: *p*-value thresholds: * <5%, ** < 1%, *** < 0.1%.

Table 10A.12. Full structural estimation for wives – 3SLS estimator

	Linear specification						**Quadratic specification**					
	Cens. sample			Uncens. sample			Cens. sample			Uncens. sample		
	β	s.e.	Sig.	β	s.e.	Sig.	β	s.e.	Sig.	β	s.e.	Sig.
Mating equation for schooling												
Dependent variable: husband's schooling												
Wife's schooling	0.565	0.014	***	0.550	0.006	***	0.417	0.044	***	0.248	0.020	***
Wife's wage	0.149	0.015	***	0.164	0.011	***	0.133	0.016	***	0.107	0.011	***
Wife's schooling (square)							0.037	0.010	***	0.086	0.005	***
Constant	0.174	0.070	*	0.125	0.061	*	0.402	0.094	***	0.673	0.070	***
Mating equation for wage												
Dependent variable: husband's wage												
Wife's wage	0.642	0.032	***	0.786	0.029	***	0.606	0.032	***	0.718	0.028	***
Wife's schooling	0.103	0.021	***	0.304	0.009	***	–0.068	0.062		0.006	0.027	
Wife's schooling (square)							0.044	0.015	**	0.087	0.007	***
Constant	2.169	0.146	***	0.884	0.166	***	2.508	0.165	***	1.489	0.167	***
Wage equation												
Dependent variable: wife's wage												
Wife's schooling	–0.034	0.036		–0.090	0.010	***	–0.001	0.038		–0.056	0.011	***
Constant	5.399	0.127	***	5.239	0.043	***	5.250	0.134	***	5.072	0.045	***
Control for inverse Mills ratio	Yes			Yes			Yes			Yes		
Control for qualification	Yes			Yes			Yes			Yes		
Control for job sector	Yes			Yes			Yes			Yes		
Control for expertise	Yes			Yes			Yes			Yes		
Control for wealth	Yes			Yes			Yes			Yes		
Control for non-labour income	Yes			Yes			Yes			Yes		
Statistics												
Subjects	6,216			14,173			6,216			14,173		
R^2 1st equation	0.412			0.400			0.418			0.417		
R^2 2nd equation	0.079			0.034			0.110			0.073		
R^2 3rd equation	0.367			0.436			0.368			0.438		

Note: *p*-value thresholds: * <5%, ** < 1%, *** < 0.1%.

Table 10A.13. Full structural estimation for young wives – 3SLS estimator

	Linear specification						**Quadratic specification**					
	Cens. sample			Uncens. sample			Cens. sample			Uncens. sample		
	β	s.e.	Sig.	β	s.e.	Sig.	β	s.e.	Sig.	β	s.e.	Sig.
Mating equation for schooling												
Dependent variable: husband's schooling												
Wife's schooling	0.527	0.029	***	0.578	0.016	***	0.892	0.179	***	0.402	0.059	***
Wife's wage	0.126	0.027	***	0.119	0.020	***	0.124	0.027	***	0.099	0.021	***
Wife's schooling (square)							-0.076	0.038	*	0.045	0.015	**
Constant	0.423	0.130	**	0.318	0.117	**	0.002	0.264		0.592	0.146	***
Mating equation for wage												
Dependent variable: husband's wage												
Wife's wage	0.297	0.060	***	0.228	0.070	**	0.305	0.060	***	0.173	0.069	*
Wife's schooling	0.137	0.046	**	0.342	0.028	***	-0.189	0.258		0.049	0.086	
Wife's schooling (square)							0.069	0.054		0.074	0.020	***
Constant	3.736	0.275	***	3.845	0.421	***	4.080	0.433	***	4.419	0.440	***
Wage Equation												
Dependent variable: husband's wage												
Wife's schooling	0.055	0.126		-0.291	0.043	***	0.049	0.126		-0.275	0.043	***
Constant	4.695	0.447	***	5.420	0.158	***	4.717	0.448	***	5.355	0.159	***
Control for inverse Mills ratio	Yes			Yes			Yes			Yes		
Control for qualification	Yes			Yes			Yes			Yes		
Control for job sector	Yes			Yes			Yes			Yes		
Control for expertise	Yes			Yes			Yes			Yes		
Control for wealth	Yes			Yes			Yes			Yes		
Control for non-labour income	Yes			Yes			Yes			Yes		
Statistics												
Subjects	1,325			2,940			1,325			2,940		
R^2 1st equation	0.306			0.322			0.310			0.327		
R^2 2nd equation	0.151			0.102			0.147			0.109		
R^2 3rd equation	0.284			0.431			0.284			0.431		

Note: p-value thresholds: * <5%, ** < 1%, *** < 0.1%.

Table 10A.14. Full structural estimation for husbands – SUR estimator

	Linear specification						**Quadratic specification**					
	Cens. sample			Uncens. sample			Cens. sample			Uncens. sample		
	β	s.e.	Sig.	β	s.e.	Sig.	β	s.e.	Sig.	β	s.e.	Sig.
Mating equation for schooling												
Dependent variable: wife's schooling												
Husband's schooling	0.585	0.011	***	0.653	0.008	***	0.422	0.042	***	0.374	0.025	***
Husband's wage	0.099	0.009	***	0.086	0.007	***	0.091	0.009	***	0.062	0.007	***
Husband's schooling (square)							0.039	0.010	***	0.076	0.006	***
Constant	0.436	0.049	***	0.249	0.040	***	0.646	0.070	***	0.618	0.049	***
Mating equation for wage												
Dependent variable: wife's wage												
Husband's wage	0.459	0.017	***	0.189	0.008	***	0.453	0.017	***	0.184	0.008	***
Husband's schooling	0.191	0.021	***	0.042	0.009	***	-0.193	0.073	**	-0.245	0.027	***
Husband's schooling (square)							0.094	0.017	***	0.080	0.007	***
Constant	2.705	0.123	***	4.609	0.055	***	3.113	0.144	***	4.864	0.059	***
Wage equation												
Dependent variable: husband's wage												
Husband's schooling	0.311	0.017	***	0.233	0.010	***	0.312	0.017	***	0.235	0.010	***
Constant	4.605	0.054	***	4.806	0.034	***	4.600	0.054	***	4.797	0.034	***
Control for qualification	Yes			Yes			Yes			Yes		
Control for job sector	Yes			Yes			Yes			Yes		
Control for expertise	Yes			Yes			Yes			Yes		
Control for wealth	Yes			Yes			Yes			Yes		
Control for non-labour income	Yes			Yes			Yes			Yes		
Statistics												
Subjects	6,093			13,915			6,093			13,915		
R^2 1st equation	0.424			0.403			0.426			0.409		
R^2 2nd equation	0.235			0.104			0.238			0.111		
R^2 3rd equation	0.377			0.363			0.377			0.363		

Note: p-value thresholds: * <5%, ** < 1%, *** < 0.1%.

Table 10A.15. Full structural estimation for young husbands – SUR estimator

	Linear specification						Quadratic specification					
	Cens. sample			Uncens. sample			Cens. sample			Uncens. sample		
	β	s.e.	Sig.	β	s.e.	Sig.	β	s.e.	Sig.	β	s.e.	Sig.
Mating equation for schooling												
Dependent variable: wife's schooling												
Husband's schooling	0.536	0.023	***	0.515	0.016	***	1.175	0.166	***	0.270	0.050	***
Husband's wage	0.040	0.017	*	0.106	0.013	***	0.048	0.017	**	0.091	0.013	***
Husband's schooling (square)							-0.135	0.035	***	0.066	0.013	***
Constant	0.946	0.100	***	0.536	0.076	***	0.156	0.225		0.828	0.092	***
Mating equation for wage												
Dependent variable: wife's wage												
Husband's wage	0.438	0.043	***	0.097	0.021	***	0.434	0.043	***	0.090	0.021	***
Husband's schooling	0.272	0.061	***	0.031	0.025		-0.744	0.382		-0.408	0.074	***
Husband's schooling (square)							0.218	0.081	**	0.122	0.019	***
Constant	1.870	0.336	***	4.972	0.130	***	3.056	0.561	***	5.343	0.142	***
Wage equation												
Dependent variable: husband's wage												
Husband's schooling	0.306	0.049	***	0.235	0.030	***	0.305	0.049	***	0.237	0.030	***
Constant	4.653	0.164	***	5.004	0.094	***	4.655	0.164	***	4.996	0.094	***
Control for qualification	Yes			Yes			Yes			Yes		
Control for job sector	Yes			Yes			Yes			Yes		
Control for expertise	Yes			Yes			Yes			Yes		
Control for wealth	Yes			Yes			Yes			Yes		
Control for non-labour income	Yes			Yes			Yes			Yes		
Statistics												
Subjects	1,278			2,852			1,278			2,852		
R^2 1st equation	0.340			0.338			0.348			0.344		
R^2 2nd equation	0.166			0.036			0.170			0.050		
R^2 3rd equation	0.276			0.270			0.276			0.270		

Note: p-value thresholds: * <5%, ** < 1%, *** < 0.1%.

10A.3. Estimate Comparison

Table 10A.16. Husbands

Estimator	3SLS				SUR			
Sample	Censored		Uncensored		Censored		Uncensored	
Selection	(C)	(Y)	(C)	(Y)	(C)	(Y)	(C)	(Y)
Mating equation for schooling								
Husband's schooling	0.590	0.480	0.665	0.494	0.608	0.492	0.663	0.537
Husband's wage	0.106	0.073	0.033	0.165	0.076	0.049	0.037	0.084
Mating equation for wage								
Dependent variable: wife's wage								
Husband's wage	1.027	0.844	0.645	0.135	0.424	0.397	0.190	0.086
Husband's schooling	0.045	0.148	–0.016	0.046	0.231	0.258	0.105	0.057
Wage equation								
Dependent variable: husband's wage								
Husband's schooling	0.400	0.307	0.404	0.349	0.383	0.315	0.361	0.364

Notes: C = complete sample, Y = young couples sample.

Table 10A.17. Wives

	3SLS				SUR			
	Censored		Uncensored		Censored		Uncensored	
	(C)	(Y)	(C)	(Y)	(C)	(Y)	(C)	(Y)
Mating equation for schooling								
Wife's schooling	0.562	0.499	0.611	0.560	0.603	0.538	0.618	0.564
Wife's wage	0.145	0.145	0.111	0.136	0.083	0.076	0.086	0.087
Mating equation for wage								
Dependent variable: wife's wage								
Wife's wage	0.681	0.353	0.838	0.191	0.327	0.199	0.402	0.166
Wife's schooling	0.114	0.146	0.410	0.437	0.241	0.191	0.397	0.437
Wage equation								
Dependent variable: husband's wage								
Wife's schooling	–0.013	0.205	–0.136	–0.130	0.125	0.287	–0.035	–0.114

Notes: C = complete sample, Y = young couples sample.

10A.4. Elasticity of Substitution

Table 10A.18. Schooling. Complete sample

Variables	Wives		Husbands	
	(1)	(2)	(1)	(2)
λ	0.529 ***	0.536 ***	0.749 ***	0.702 ***
	0.081)	(0.067)	(0.038)	(0.026)
θ	0.668 ***	0.727 ***	0.963 ***	0.968 ***
	(0.121)	(0.092)	(0.019)	(0.010)
η	–0.617 ***	–0.444 ***	0.423 **	0.602 ***
	(0.157)	(0.128)	(0.160)	(0.097)
Elasticity σ				
Coefficient	0.619	0.693	1.734	2.514
Upper bound	0.685	0.760	2.399	3.331
Lower bound	0.564	0.636	1.357	2.019
p-value for $H_0 : \eta < 0$	1.000	1.000	0.004	0.000
N	19,887	19,887	19,887	19,887
R^2	0.917	0.917	0.921	0.920

Notes:
Dependent variable: Years of completed schooling. Standard errors in parentheses.
p-value thresholds: * < 5%, ** < 1%, *** < 0:1%.
(1) Non-linear Least Squares (NLS).
(2) Non-linear Seemingly Unrelated Estimate (NLSUR).

Table 10A.19. Schooling. Young couple sample

Variables	Wives		Husbands	
	(1)	(2)	(1)	(2)
λ	0.664 ***	0.658 ***	0.759 ***	0.727 ***
	(0.098)	(0.075)	(0.049)	(0.035)
θ	0.858 ***	0.886 ***	0.968 ***	0.973 ***
	(0.096)	(0.063)	(0.025)	(0.014)
η	–0.155	0.002	0.448	0.630 ***
	(0.227)	(0.170)	(0.255)	(0.163)
Elasticity σ				
Coefficient	0.866	1.002	1.810	2.700
Upper bound	1.077	1.208	3.367	4.816
Lower bound	0.724	0.856	1.238	1.876
p-value for $H_0 : \eta < 0$	0.753	0.496	0.040	0.000
N	3,966	3,966	3,966	3,966
R^2	0.931	0.931	0.933	0.932

Notes:
Dependent variable: Years of completed schooling. Standard errors in parentheses.
p-value thresholds: * < 5%, ** < 1%, *** < 0:1%.
(1) Non-linear Least Squares (NLS).
(2) Non-linear Seemingly Unrelated Estimate (NLSUR).

Table 10A.20. Wage. Complete sample

Variables	Wives (1)	Wives (2)	Husbands (1)	Husbands (2)
λ	6.120 ***	6.152 ***	27.350 ***	24.830 ***
	(1.524)	(1.430)	(3.882)	(3.608)
θ	0.331 **	0.372 **	0.939 ***	0.930 ***
	(0.126)	(0.120)	(0.046)	(0.047)
η	-0.515 ***	-0.421 **	0.577 *	0.604 **
	(0.155)	(0.138)	(0.230)	(0.205)
Elasticity σ				
Coefficient	0.660	0.704	2.364	2.528
Upper bound	0.735	0.780	5.181	5.253
Lower bound	0.599	0.641	1.532	1.665
p-value for $H_0 : \eta < 0$	1.000	0.999	0.006	0.002
N	19,887	19,887	19,887	19,887
R^2	0.762	0.761	0.654	0.653

Notes:
Dependent variable: Years of completed schooling. Standard errors in parentheses.
p-value thresholds: * < 5%, ** < 1%, *** < 0:1%.
(1) Non-linear Least Squares (NLS).
(2) Non-linear Seemingly Unrelated Estimate (NLSUR).

Table 10A.21. Wage. Young couple sample

Variables	Wives (1)	Wives (2)	Husbands (1)	Husbands (2)
λ	26.627 ***	26.525 ***	28.884 ***	27.251 ***
	(0.291)	(0.256)	(3.961)	(3.472)
θ	0.993	0.775	0.969 ***	0.966 ***
	.	.	(0.043)	(0.035)
η	-44.061	-63.913	0.573	0.644 *
	.	.	(0.414)	(0.317)
Elasticity σ				
Coefficient	0.022	0.015	2.342	2.807
Upper bound	0.022	0.015	75.463	25.647
Lower bound	0.022	0.015	1.190	1.485
p-value for $H_0 : \eta < 0$	.	.	0.083	0.021
N	3,966	3,966	3,966	3,966
R^2	0.748	0.748	0.714	0.714

Notes:
Dependent variable: Years of completed schooling. Standard errors in parentheses.
p-value thresholds: * < 5%, ** < 1%, *** < 0:1%.
(1) Non-linear Least Squares (NLS).
(2) Non-linear Seemingly Unrelated Estimate (NLSUR).

NOTES

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1. The observed degree of assortative mating also depends on the marginal distribution of traits in the two sides of the market, since a given degree of assortative mating is always observed in the data because of random matching. Using marriage-market-level data, it is possible to decompose sorting between random and systematic factors. See Sundaram (2004) and Liu and Lu (2006).
2. These nonlinearities will be discussed in more detail in Section 10.5.2.
3. Estimation results for husbands are not displayed here, but are available upon demand.
4. For other details on the structure of mating in Italy see Filoso (2008).
5. I thank Graziella Bertocchi for bringing this to my attention.

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